Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 97 (2014) 85 – 94

Procedia Engineering

www.elsevier.com/locate/procedia

12th GLOBAL CONGRESS ON MANUFACTURING AND MANAGEMENT, GCMM 2014

Grey Fuzzy Multiobjective Optimization of Process Parameters for CNC Turning of GFRP/Epoxy Composites

Hari Vasudevan[a] , Naresh C.Deshpande[a]*, Ramesh R. Rajguru [b]

[a] *Production Engineering Department, Dwarkadas J. Sanghvi College of Engineering, Vile Parle (w), Mumbai – 400 056, INDIA.*
[b]*Mechanical Engineering Department, Dwarkadas J. Sanghvi College of Engineering, Vile Parle (w), Mumbai – 400 056, INDIA.*

Abstract

For obtaining close fits and tolerances, certain amount of machining has to be carried out on GFRP (Glass Fibre Reinforced Plastic) composites, produced by primary manufacturing processes. A number of cylindrical GFRP composite parts are finish machined by turning. These include axles, bearings, spindles, rolls and steering columns. There is always a tradeoff between quality and productivity during machining operations. Hence it becomes essential to evaluate the optimal cutting parameters setting in order to satisfy these opposing requirements. In this study, a hybrid multiobjective optimization algorithm involving grey and fuzzy coupled with Taguchi methodology is used. Four process parameters, each at three levels are selected for the study viz. cutting tool nose radius, cutting speed, feed rate and depth of cut. Surface roughness parameter Ra, tangential cutting force Fz and material removal rate MRR are the chosen output performance measures. The experimental plan is laid according to Taguchi's orthogonal array L27. Woven fabric based GFRP/ Epoxy tubes produced using hand layup process are finish turned using PCD cutting tool. Grey relational coefficients of the three performance measures are converted into a single multi performance characteristics index (MPCI) using Mamdani type fuzzy inference system. This MPCI is then optimized using Taguchi analysis. The parameter combination of A2B1C1D3, i.e. tool nose radius of 0.8 mm, cutting speed of 120 m/min, feed rate of 0.05 mm/rev and depth of cut of 1.6 mm, is evaluated as the optimum combination. The confirmatory experiment at these settings gave maximum value of MPCI, validating the results.

Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014

Keywords: Multiobjective Optimization; GFRP/Epoxy; Woven fabric; Grey relational coefficient; Fuzzy inference system

* Corresponding author. Tel.: +91-022-26107010; fax: +91-022-26194988.
E-mail address: ncdeshpande72@yahoo.co.in

Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014
doi:10.1016/j.proeng.2014.12.228

1. Introduction

Machining aspects in the case of glass fiber reinforced plastics differ in comparison to that of metals. Shearing due to plastic deformation is the mechanism by which most homogeneous metals are machined. Machining of GFRP composite involves uncontrolled and intermittent fracture. Oscillating cutting forces are typical, because of the intermittent fracture of the fibers [1]. High cutting force is responsible for high cutting tool wear; low tool life and unstable machine tool, which further affects dimensional accuracy. Hence minimization of cutting force is important. When machining operations are performed, both quality and productivity are important. Dimensional accuracy and surface finish are two important measures of quality of any machined product. High material removal rate (MRR) signifies high productivity. Usually high dimensional accuracy and finish are associated with low MRR. Hence it is important to find out the optimum combination of cutting parameters setting to satisfy these opposing needs of quality and productivity.

Isik and kentli [2] proposed a multiple criteria optimization approach using sensitivity. Minimizing cutting forces and maximizing the material removal were considered as objectives, while turning of unidirectional glass fiber reinforced polyester rods. Palanikumar et al. [3] used grey relational grade & Taguchi method for minimizing tool wear, surface roughness and specific cutting pressure, while maximizing material removal. They carried out turning on GFRP/Epoxy composites using carbide (K10) tool. Krishnamoorthy et al. [4] applied grey fuzzy logic for optimization of drilling process parameters of carbon fibre reinforced plastic composite plates. Rajmohan et al. [5] used grey fuzzy algorithm to optimize the machining parameters, while drilling of hybrid aluminium metal matrix composites.

Machinability of composite materials depends upon the fibre type, resin type, fibre orientation and manufacturing method. It is observed from the extant literature survey that, despite the wide scale applications of woven glass fiber reinforced epoxy composites manufactured by hand lay-up process; so far, no systematic attempt has been made to understand their machining aspects. Also, although many researchers have used various multi criteria decision making algorithms for cutting parameters optimization of GFRP/E composites, the proposed algorithm with grey relational coefficient and fuzzy inference system has not been utilised. This study is an attempt to bridge these gaps.

2. Methodology

The methodology adopted for this study is as shown below in Fig. 1.

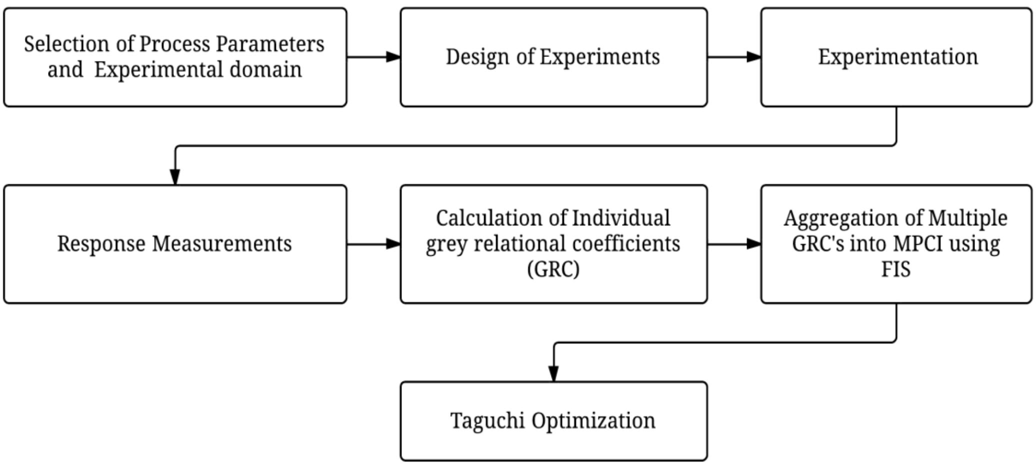

Fig. 1. Methodology used for the study

2.1. Experimentation

The work material selected for the study was glass fibre reinforced epoxy composite. The plain weave type woven fabric reinforcement was made from E-glass. The areal weight of the fabric was 180±5 gm/m^2 and the thickness was 0.18 mm. Epoxy resin manufactured by Huntsman, product Araldite LY3297 and hardener Aradur 3298 was used as polymer matrix material. The cylindrical work specimens were 50 mm long, with inner diameter of 20 mm and outer diameter of 55 mm. They were manufactured using hand lay-up process and cured at room temperature. The volume fraction of the reinforcement used was 70%. The work pieces before & after machining are as shown in Fig. 2 (a & b). Fine grade poly crystalline diamond (PCD) inserts were used for cutting. The three diamond shaped inserts had nose radius of 0.4 mm, 0.8 mm and 1.2 mm respectively. Ace Jobber XL CNC lathe machine having maximum spindle speed of 4000 rpm and maximum power of 7.5 KW was used for the turning operation. The machining was carried out without any coolant. The selected process parameters and their levels are as given in Table 1.

Taguchi's design of experiments (DOE) was used to plan the experiments. If any nonlinear relationship exists among the process parameters, then it can only be revealed by considering more than two levels of the parameters [6]. Thus each selected parameter is analyzed at three levels. The total degrees of freedom (DOF) for four parameters, each at three levels are eight. Hence, a three level orthogonal array (OA) with at least eight DOF is to be selected. The L27 OA (DOF = 26) was thus selected for this case study. The factors were assigned to column numbers 1, 2, 5 and 8 respectively. The unassigned columns were treated as error. Randomization principle was used to carry out the experiments. One repetition for each of the 27 trials was performed. Specially designed mandrel was used to mount the work specimens. The response measures selected were, surface roughness parameter Ra, tangential cutting force Fz and material removal rate MRR. Taylor Hobson Talysurf-5 surface roughness tester was used to measure the roughness parameter Ra. The cut off length of 0.8 mm was set on this instrument. The raw data was filtered using Gaussian filter. Data acquisition was accomplished by connecting this profiler to computer and using SESURF software. Kistler piezo electric dynamometer of type-5233A, with built in charge amplifier up to 10 KN and a least count of 1mN was used for the measurement of tangential cutting force. This dynamometer was connected to the computer equipped with Kistler Dynoware type- 2825A software for data acquisition purpose. The material removal rate was calculated as per Eq. (1), by measuring the weight of component before and after turning operation, with precision digital weighing machine and recording the machining time with a stop watch.

$$M.R.R. = \frac{W_i - W_f}{t_m}(gms/\sec) \quad (1)$$

Where, W_i is the initial weight of work specimen in gms; W_f is the final weight of work specimen after machining in gms. and t_m is the machining time in sec. Table 2. shows L27 OA and the measured values of the three responses.

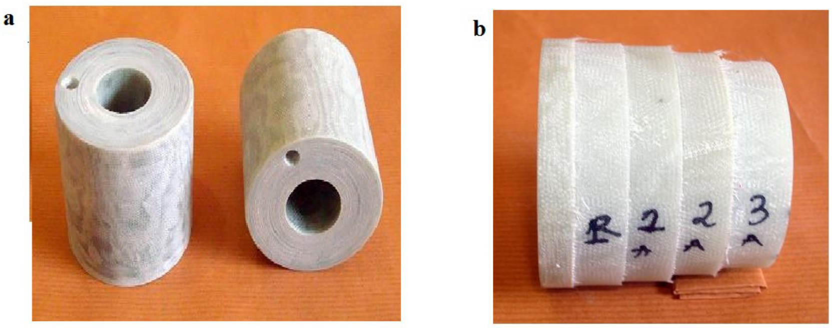

Fig. 2. (a) Work specimens before machining; (b) Work specimen after machining

Table 1. Selected process parameters and their levels.

Process parameters designation	Process parameters	Units	Levels		
			Level 1	Level 2	Level 3
A	Tool nose radius	mm	0.4	0.8	1.2
B	Cutting speed	m/min	120	160	200
C	Feed rate	mm/rev	0.05	0.15	0.25
D	Depth of cut	mm	0.6	1	1.6

Table 2. Taguchi's L27 OA and the measured mean values of the responses.

Trial No.	Design of experiments (coded)				Ra (microns)	Fz (N)	MRR (gms/sec)
	A	B	C	D			
1	1	1	1	1	2.5802	9.2450	0.1398
2	1	1	2	2	2.4347	38.2350	0.6825
3	1	1	3	3	3.6033	80.6850	0.8889
4	1	2	1	2	3.0963	12.4650	0.2372
5	1	2	2	3	2.0938	54.0150	0.8721
6	1	2	3	1	3.2542	28.1650	0.5952
7	1	3	1	3	2.3977	16.7050	0.4737
8	1	3	2	1	2.6735	17.7300	0.4960
9	1	3	3	2	3.1297	48.9000	1.0000
10	2	1	1	1	2.3362	7.4300	0.1037
11	2	1	2	2	2.6505	30.2150	0.4879
12	2	1	3	3	2.6837	74.4050	2.8889
13	2	2	1	2	2.1363	12.4800	0.1630
14	2	2	2	3	1.9337	47.7300	0.6869
15	2	2	3	1	3.2880	24.4450	0.6389
16	2	3	1	3	2.0878	17.3950	0.6490
17	2	3	2	1	2.1220	17.4250	0.4286
18	2	3	3	2	2.2728	42.8650	1.7778
19	3	1	1	1	3.7797	10.5750	0.1198
20	3	1	2	2	1.9260	26.3700	0.5794
21	3	1	3	3	1.6973	68.4350	1.0556
22	3	2	1	2	2.1115	15.1800	0.4022
23	3	2	2	3	2.5267	49.7900	0.8426
24	3	2	3	1	2.8962	21.0750	1.0000
25	3	3	1	3	1.7735	18.5550	0.4240
26	3	3	2	1	2.2870	21.5750	0.4101
27	3	3	3	2	2.6573	43.2300	1.1111

2.2. Optimization

2.2.1. Grey relational analysis (GRA)

The mathematical approach to deal with incomplete and uncertain information is given by grey systems theory. In order to assist the decision making and results prediction while studying uncertain systems, this concept was proposed by Deng. In grey systems theory, white means having all the information, where as black means complete absence of information. For intermediate level of information the system is grey. This theory is applied in various ways in different domains like grey relational analysis, grey modelling, grey programming, grey control and grey clustering.

The first step in GRA is called as grey relational generation. The units of different response attributes can be different. Some of attributes may have very large range and it is also possible that the targets and directions of these attributes are different. Therefore, processing of all response values for every alternative into a comparability sequence is important. This processing is similar to the normalization process and is called as grey relational generation in GRA. For a multiobjective decision making problem, if there are *m* alternatives and *n* response attributes, the i^{th} alternative can be expressed as $Y_i = (y_{i1}, y_{i2}, ..., y_{ij}, ..., y_{in})$, where y_{ij} is the performance value of attribute *j* for alternative *i*. Depending upon the type of response, the term Y_i can be translated into the comparability sequence $X_i = (x_{i1}, x_{i2}, ..., x_{ij},..., x_{in})$ by use of one of the Eqs. (2 - 3) [7].

If the response is of larger the better type then Eq. (2) is used for normalization. In the present study, this is used for material removal rate (MRR).

$$x_{ij} = \frac{y_{ij} - Min\left\{y_{ij}, i = 1,2,....,m\right\}}{Max\left\{y_{ij}, i = 1,2,....,m\right\} - Min\left\{y_{ij}, i = 1,2,....,m\right\}} \tag{2}$$

If the response is of smaller the better type then Eq. (3) is used for normalization. In the present study, this is used for tangential cutting force F_z and roughness parameter R_a.

$$x_{ij} = \frac{Max\left\{y_{ij}, i = 1,2,....,m\right\} - y_{ij}}{Max\left\{y_{ij}, i = 1,2,....,m\right\} - Min\left\{y_{ij}, i = 1,2,....,m\right\}} \tag{3}$$

After the grey relational generation procedure, all performance values will be normalized into {0, 1}. Therefore the alternative with performance values closer to or equal to 1 is the best one. The reference sequence X_0 is defined as $(x_{01}, x_{02}, ..., x_{0j}, ..., x_{0n}) = (1,1,...,1,...,1)$. The aim is to find the alternative, whose comparability sequence is closest to this reference sequence.

Grey relational coefficient is used for determining the closeness between x_{ij} and x_{0j}. The larger grey relational coefficient means, x_{ij} is closer to x_{0j}. The grey relational coefficient can be calculated by Eq.(4) [7].

$$\gamma\left(x_{oj}, x_{ij}\right) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{ij} + \zeta\Delta_{\max}} \quad \text{for } i = 1,2,\ldots\ldots,m \qquad j = 1,2,\ldots\ldots,n \tag{4}$$

Where, $\gamma(x_{oj}, x_{ij})$ is the grey relational coefficient between x_{oj} and x_{ij} and

$$\Delta_{ij} = \left|x_{oj} - x_{ij}\right|, \Delta_{\min} = Min\left\{\Delta_{ij}, i = 1,2,....,m; j = 1,2,....,n\right\}, \Delta_{\max} = Max\left\{\Delta_{ij}, i = 1,2,....,m; j = 1,2,....,n\right\},$$

ζ is the distinguishing coefficient, $\zeta \in \{0,1\}$. Here ζ is taken as 0.5.

Then, the grey relational grade is computed by averaging the grey relational coefficient corresponding to each response attribute by using Eq. (5) [7].

$$\Gamma\left(x_o, x_i\right) = \frac{1}{n}\sum_{j=1}^{n} w_j \gamma\left(x_{oj}, x_{ij}\right) \quad \text{for } i = 1,2,\ldots\ldots,\mathrm{m} \tag{5}$$

Where, $\Gamma(x_o, x_i)$ is the grey relational grade between x_o and x_i. This grade is treated as a single quality index and the alternative having maximum grade is usually chosen as optimum. The assignment of proper response weight w_j is a subjective decision and varies from person to person. Results gained by this approach could be faulty due to subjective nature of response weights. Therefore, even a small change in priority weight may change the optimal setting. Many scholars have used this approach for multi criteria optimization. Prasanna et al. [8] used grey relational analysis and mathematical modeling to optimize multiple performance criteria like thrust force, overcut, circularity and taper, while drilling of small holes in titanium alloy plates. Lohithaksha et al. [9] applied GRA to optimize machining parameters for end milling of Inconel 718 super alloy. Ahmet and Kenan [10] used GRA to optimize drilling parameters for boron carbide fiber reinforced metal matrix composites. Emel and Babur [11] applied grey relational analysis to optimize machining parameters while micro milling of Al 7075 material with ball nose end mill .

To avoid the uncertainty due to response weights, fuzzy inference system is used in the present study to couple grey relational coefficients into a single performance index i.e. multi performance criteria index (MPCI).

2.2.2. Fuzzy inference system (FIS)

Prof. Lotfi A. Zedah [12] introduced the concepts of fuzzy sets and systems. A fuzzy inference system uses fuzzy set theory to map inputs to outputs. Shabgard et al. [13] used a fuzzy-based algorithm for prediction of material removal rate, tool wear ratio and surface roughness in the electrical discharge machinng (EDM) and ultrasonic-assisted EDM processes. Azmi [14] used Mamdani type fuzzy inference to model the useful tool life of end mill cutter while machining composite materials. Majumder [15] used a hybrid approach using fuzzy logic and particle swarm optimization (PSO) for optimizing the process parameters in the electric discharge machining of stainless steel.

There are basically two types of fuzzy inference systems viz. Mamdani and Sugino. Mamdani type system gives the fuzzy output, which if required has to be converted into crisp value using defuzzification method. It is intuitive and suitable to human inputs and so is widely used. Sugino type inference system gives an output that is either constant or a weighted linear model. It can only be used to model those systems in which the output membership functions are either linear or constant. In the present study, Mamdani type fuzzy system is used. The important steps involved in the creation of this system are viz. fuzzification, rules evaluation and defuzzification.

Fuzzification involves conversion of crisp input values into imprecise quantities like 'large', 'medium', 'high' etc., with a degree of belongingness to it. Typically, the value ranges from 0 to 1. These quantities are also called as membership functions. They depict the fuzziness in the fuzzy set graphically. There are numerous methods for depicting these membership functions. Triangular, Trapezoidal and Gaussian are some types of membership function shapes. There is no standard method for choosing the proper shape of the membership functions for control variables.

In the next step of rules evaluation, the rule base containing a number of fuzzy IF-THEN rules is used to map the inputs to the output membership function. The rules set used for the present fuzzy inference system are given in Table 3. Defuzzification involves the conversion of fuzzy output into a crisp value. There are numerous methods for defuzzifying fuzzy sets. Centroid of area is the most widely used defuzzification method and is also used for the present study.

Table 3. Rule set used for the FIS.

Rule	IF GRC-Ra is	AND GRC-Fz is	AND GRC-MRR is	THEN MPCI is	Rule	IF GRC-Ra is	AND GRC-Fz is	AND GRC-MRR is	THEN MPCI is
R1	Low	Low	Low	very low	R33	High	High	Low	high
R2	Low	Low	Medium	very low	R34	Medium	Low	Medium	low
R3	Low	Low	High	Low	R35	High	Low	Medium	medium
R4	Low	Medium	Low	very low	R36	Low	Medium	Medium	low
R5	Low	Medium	Medium	Low	R37	High	Medium	Medium	high
R6	Low	Medium	High	Medium	R38	Low	High	Medium	medium
R7	Low	High	Low	Low	R39	High	High	Medium	very high
R8	Low	High	Medium	Medium	R40	Low	Low	High	low
R9	Low	High	High	High	R41	Medium	Low	High	medium
R10	Medium	Low	Low	very low	R42	Low	Medium	High	medium
R11	Medium	Low	Medium	Low	R43	Medium	Medium	High	high
R12	Medium	Low	High	Medium	R44	Low	High	High	high
R13	Medium	Medium	Low	Low	R45	Medium	High	High	very high
R14	Medium	Medium	Medium	Medium	R46	Medium	Low	Low	very low
R15	Medium	Medium	High	High	R47	Medium	Low	Medium	low
R16	Medium	High	Low	Medium	R48	Medium	Low	High	medium
R17	Medium	High	Medium	High	R49	High	Low	Low	low
R18	Medium	High	High	very high	R50	High	Low	Medium	medium
R19	High	Low	Low	Low	R51	High	Low	High	high
R20	High	Low	Medium	Medium	R52	Low	Medium	Low	very low
R21	High	Low	High	High	R53	Low	Medium	Medium	low
R22	High	Medium	Low	Medium	R54	Low	Medium	High	medium
R23	High	Medium	Medium	High	R55	High	Medium	Low	medium
R24	High	Medium	High	very high	R56	High	Medium	Medium	high
R25	High	High	Low	Medium	R57	High	Medium	High	very high
R26	High	High	Medium	very high	R58	Low	High	Low	low
R27	High	High	High	very high	R59	Low	High	Medium	medium
R28	Medium	Low	Low	very low	R60	Low	High	High	high
R29	High	Low	Low	Low	R61	Medium	High	Low	medium
R30	Medium	Medium	Low	Low	R62	Medium	High	Medium	high
R31	High	Medium	Low	Medium	R63	Medium	High	High	very high
R32	Medium	High	Low	Medium					

In this study, fuzzy inference system is used to estimate the MPCI, when values of grey relational coefficient are given as inputs to the system. This is a multi input single output type of model as shown in Fig. 3.The number of GRCs obtained in grey relational analysis are used as inputs. In three inputs (GRCs) and one output (MPCI) system, both the inputs and the output are taken in the form of linguistic format.

A linguistic variable is a variable, whose values are words or sentences in a natural or man-made language. In the proposed model, Gaussian type membership functions are used for input as well as output variable, as shown in Fig. 4 & Fig. 5 respectively. Individual grey relational coefficient values of the responses and the calculated MPCI are as given in Table 4.

Table 4. Individual grey relational coefficient values of the responses and MPCI.

Sr. No.	Individual grey relational coefficient values of the responses			MPCI	S/N ratio
	GRC - Fz	GRC - Ra	GRC - MRR		
1	0.953	0.541	0.336	0.687	-3.26087
2	0.543	0.585	0.387	0.489	-6.21382
3	0.333	0.353	0.410	0.44	-7.13095
4	0.879	0.427	0.344	0.668	-3.50447
5	0.440	0.724	0.408	0.602	-4.40807
6	0.639	0.401	0.378	0.515	-5.76386
7	0.798	0.598	0.366	0.619	-4.16619
8	0.781	0.516	0.368	0.609	-4.30765
9	0.469	0.421	0.424	0.5	-6.0206
10	1.000	0.620	0.333	0.684	-3.29888
11	0.616	0.522	0.367	0.484	-6.30309
12	0.354	0.514	1.000	0.702	-3.07326
13	0.879	0.703	0.338	0.667	-3.51748
14	0.476	0.815	0.387	0.656	-3.66192
15	0.683	0.396	0.382	0.554	-5.1298
16	0.786	0.727	0.383	0.645	-3.80881
17	0.786	0.710	0.361	0.619	-4.16619
18	0.508	0.644	0.556	0.539	-5.36822
19	0.921	0.333	0.335	0.611	-4.27918
20	0.659	0.820	0.376	0.649	-3.75511
21	0.375	1.000	0.432	0.721	-2.84129
22	0.825	0.715	0.359	0.634	-3.95821
23	0.464	0.557	0.405	0.5	-6.0206
24	0.729	0.465	0.424	0.606	-4.35055
25	0.767	0.932	0.361	0.727	-2.76931
26	0.721	0.638	0.360	0.56	-5.03624
27	0.506	0.520	0.439	0.5	-6.0206

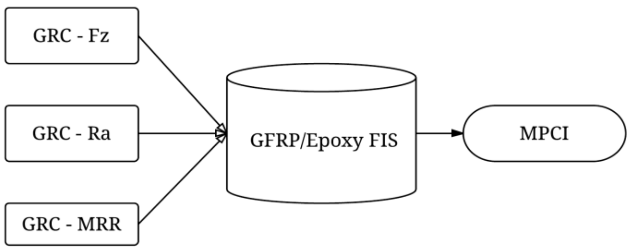

Fig. 3. The FIS model

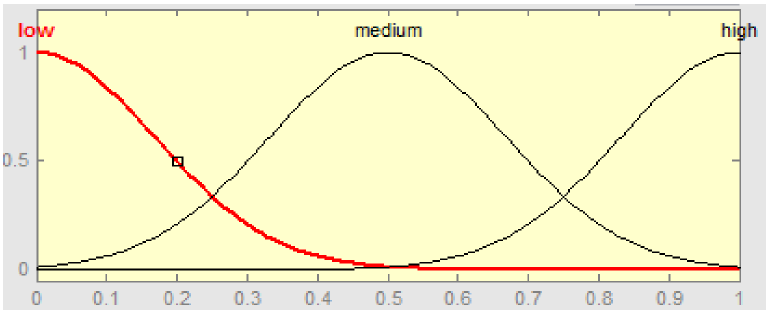

Fig. 4. Membership functions of the inputs

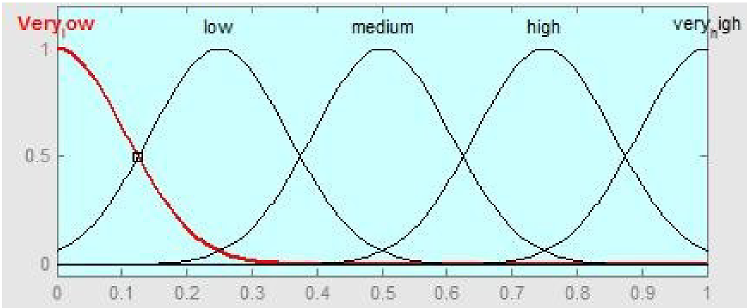

Fig. 5. Membership functions of the output MPCI

2.2.3. Taguchi optimization

To determine the optimal parameter settings, it is required to find out the highest MPCI. Optimization (maximization) of MPCI has been carried out using Taguchi method. Taguchi method converts response value into corresponding S/N ratio. The Signal-to-Noise (S/N) ratio is the ratio of mean to deviation of the response from targeted value. Therefore, in Taguchi analysis the optimal parametric combination is determined by incorporating higher-the better criteria of the response S/N ratio. Optimal parametric combination has been evaluated from the plot in Fig.6. The parameter combination of A2B1C1D3, i.e. tool nose radius of 0.8 mm, cutting speed of 120 m/min, feed rate of 0.05 mm/rev and depth of cut of 1.6 mm, is evaluated as the optimum combination. The estimated mean of the response characteristic S/N ratio (η) could be computed by using the following Eq. (6) [16]. Where $\bar{\eta}$ = overall mean of S/N ratio (η) for MPCI, A_2 = average value of S/N ratio (η) for MPCI at second level of nose radius, C_1 = average value of S/N ratio (η) for MPCI at first level of feed and D3 = average value of S/N ratio (η) for MPCI at third level of depth of cut. A, C & D are the most significant factors, affecting the S/N ratio (η) for MPCI.

$$\eta_{opt} = \bar{\eta} + (A_2 - \bar{\eta}) + (C_1 - \bar{\eta}) + \left(D_3 - \bar{\eta}\right) \tag{6}$$

Predicted value (S/N Ratio) of MPCI becomes −2.6504 (highest among all entries of values in Table 4.), whereas in confirmatory test it has been computed as −2.4048. Hence the quality has improved by using this optimal setting (increment of S/N ratio).

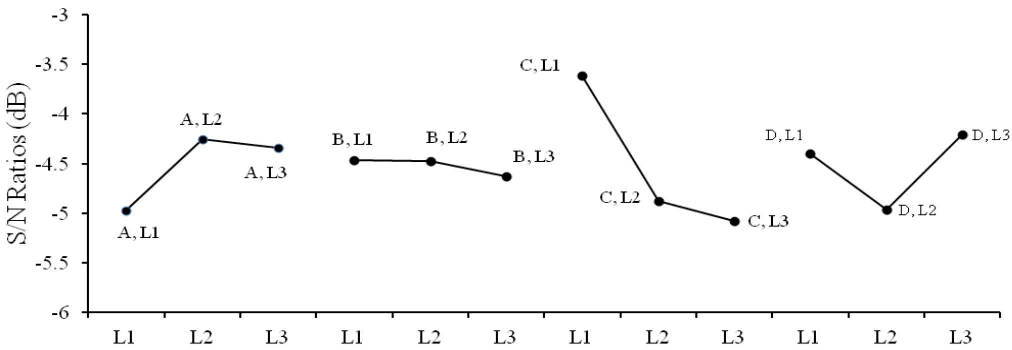

Fig. 6. Main effects plot of S/N ratios for MPCI

3. Conclusion

In this study, a fuzzy rule based model has been developed using three input variables and one output variable i.e. MPCI. By this way, a multi-response optimization problem has been converted into an equivalent single objective optimization problem, which has been solved by Taguchi philosophy. The proposed procedure is simple and effective in developing a robust finish turning process for GFRP/Epoxy composites. The proposed approach converts numerical response into a linguistic term so that the issue of response correlation could be avoided.

References

[1] Jamal Y. Sheikh-Ahmad, Machining of Polymer Composites, Springer, New York, 2009.
[2] Işık B. & Kentli A., Multicriteria optimization of cutting parameters in turning of UD-GFRP materials considering sensitivity, Int J Adv Manuf Technol. 44 (2009)1144–1153.
[3] Palanikumar K., Karunamoorthy L. & Karthikeyan R., Multiple performance optimization of machining parameters on the machining of GFRP composites using carbide (K10) tool, Materials and Manufacturing Processes, 21:8 (2007) 846-852.
[4] Krishnamoorthy A, Boopathy R.S., Palanikumar K., Davim P.J., Application of grey fuzzy logic for the optimization of drilling parameters for CFRP composites with multiple performance characteristics, Measurement 45 (2012) 1286–1296.
[5] Rajmohan T., Palanikumar K., Prakash S., Grey-fuzzy algorithm to optimise machining parameters in drilling of hybrid metal matrix composites, Composites: Part B 50 (2013) 297–308.
[6] Byrne D. M. and S. Taguchi, The Taguchi approach to parameter design, Quality Progress, 20:12 (1987) 19-26.
[7] Kuo Y., Yang T., Huang G., The use of grey relational analysis in solving multiple attribute decision-making problems, Computers & Industrial Engineering 55 (2008) 80–93.
[8] Prasanna J., Karunamoorthy L., Venkat Raman M., Prashanth S., Raj Chordia D., Optimization of process parameters of small hole dry drilling in Ti–6Al–4V using Taguchi and grey relational analysis, Measurement 48 (2014) 346–354.
[9] Lohithaksha M., Ramanujam R., Venkatesan K., Jerald J., Optimization of machining parameters for end milling of Inconel 718 super alloy using Taguchi based grey relational analysis, Procedia Engineering 64 (2013) 1276 – 1282.
[10] Taskesen A., Kutukde K., Experimental investigation and multi-objective analysis on drilling of boron carbide reinforced metal matrix composites using grey relational analysis, Measurement 47 (2013) 321–330.
[11] Kuram E., Ozcelik B., Multi-objective optimization using Taguchi based grey relational analysis for micro-milling of Al 7075 material with ball nose end mill, Measurement 46 (2013) 1849–1864.
[12] Zadeh L. A., Fuzzy sets, Information and Control, 8:3 (1965) 338-353.
[13] Shabgard M.R., Badamchizadeh M.A., Ranjbary G. and Amini K, Fuzzy approach to select machining parameters in electrical discharge machining (EDM) and ultrasonic-assisted EDM processes, Journal of Manufacturing Systems, 32 (2013) 32– 39.
[14] Azmi A. I., Design of fuzzy logic model for the prediction of tool performance during machining of composite materials, Procedia Engineering, 38 (2012) 208-217.
[15] Majumder Arindam, Process parameter optimization during EDM of AISI 316 LN stainless steel by using fuzzy based multi-objective PSO, Journal of Mechanical Science and Technology, 27 (2013) 2143-2151.
[16] Madhav S. Phadke, Quality Engineering Using Robust Design, P T R Prentice-Hall, New Jersey, 1989.